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Defending Tor from Network Adversaries: A Case Study of Network Path Prediction

Abstract: The Tor anonymity network has been shown vulnerable to traffic analysis attacks by autonomous systems and Internet exchanges, which can observe different overlay hops belonging to the same circuit. We evaluate whether network path prediction techniques provide an accurate picture of the threat from such adversaries, and whether they can be used to avoid this threat. We perform a measurement study by collecting 17.2 million traceroutes from Tor relays to destinations around the Internet. We compare the collected traceroute paths to predicted paths using state-of-the-art path inference techniques. We find that only 20.0% of predicted paths match paths seen in the traceroutes. We also consider the impact that prediction errors have on Tor security. Using a simulator to choose paths over a week, our traceroutes indicate a user could expect 10.9% of paths to contain an AS compromise and 0.9% to have an IX compromise with default Tor selection. We find modifying the path selection to choose paths predicted to be safe still presents a 5.3–11% chance of compromise in a week while making 5.1% of paths fail with 96% failing unnecessarily due to false positives in path inferences. Our results demonstrate more measurement and better path prediction is necessary to mitigate the risk of AS and IX adversaries to Tor.

Keywords: Autonomous Systems; Internet Exchanges; Tor

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1 Introduction

The Tor network for anonymous communication [14] is susceptible to end-to-end timing attacks [33], which allow an adversary who observes traffic from a client to the first Tor router

and at the same time traffic from the last Tor router to the destination to deanonymize the connection. Both of these paths traverse a number of Internet routers that belong to various organizations, leaving the possibility that a single network operator running an autonomous system (AS) or an Internet exchange (IX) will be in the position to observe both paths and thus carry out the end-to-end timing attack [15, 17, 22, 23, 30]. This threat is made more likely by the concentration of Internet traffic at Tier 1 ISPs and high-volume IXes.

To assess the vulnerability of Tor to AS and IX adversaries, it is necessary to predict the paths that traffic takes on the Internet. Previous work characterizing this threat has relied chiefly on AS-level routing predictions [31]. Such predictions are well known to be incomplete and imprecise, producing erroneous path predictions. Our goal is to evaluate the impact of these errors on the anonymity of Tor. In particular, we are concerned with two research questions:

- Are AS-level routing predictions suitable for characterizing the threat of AS and IX adversaries in Tor?
- Can AS-level routing predictions be used to construct Tor paths that avoid AS and IX adversaries (as has been suggested in previous work [5, 15])?

To answer these questions, we performed a measurement study, collecting *traceroute* probes from Tor relays to obtain a more accurate picture of Internet paths actually used by network traffic. In comparing results from traceroutes to state-of-the-art path prediction, we found that the prediction accuracy was notably worse than previously measured, despite the fact that we are interested in a simplified prediction problem looking for the *set* of ASes (or IXes) on a path, rather than the exact sequence. The errors include both extraneous ASes and IXes in the prediction that are not seen in traceroutes and, more worryingly, ASes and IXes in the traceroutes that are missing from the prediction. It is possible to produce an overestimate of the AS and IX sets by considering several of the most likely paths produced by the prediction algorithm, rather than just the top one. Such overestimates reduce but do not eliminate the problem of missing ASes and IXes, at the cost of significantly increasing the number of extraneous predictions.

We next analyze the impact of these prediction errors on the vulnerability of Tor to AS- and IX-level adversaries, with the help of a simulator that faithfully reconstructs Tor paths

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that may have been chosen by a Tor user.¹ We find that AS and IX path prediction significantly overestimates the threat of vulnerability to such adversaries; at the same time, most users do run a significant risk of compromise by an AS-level adversary as determined from the traceroute data, whereas IX-level adversaries affect only a small fraction of paths.

We then modify our simulator to specifically avoid selecting paths that are vulnerable to AS or IX adversaries based on predictions, as has been previously suggested. We show that this significantly limits the choice of paths and frequently results in *no* paths being available for use while following the Tor practice of maintaining a long-term fixed set of entry guards into the network. These limits would require reconsidering the already complex set of tradeoffs in the design of the mechanisms for selecting and updating the set of entry guards used in Tor [16]; we note that the situation is made worse by the recent move towards using a single entry guard instead of 3 [13].

On the other hand, we find that many of these failures are a consequence of over-prediction, as we are often able to find suitable non-vulnerable paths in our traceroute data set despite covering only a fraction of the Tor relays. Our work suggests that a defense based on proactive path measurement, rather than AS path models, is likely to be more practical and offer better security guarantees.

2 Background

2.1 Tor

Tor is a popular system for anonymous communication online [14]. Tor consists of a network of volunteer *relays* that form an overlay network and forward traffic sent by users running Tor clients. In February 2015, it contained approximately 7 000 relays and transferred around 70 Gbps of data for a user population estimated at over 2 000 000.²

Tor uses *onion routing* to achieve anonymity. A client sets up a connection to a destination by choosing a sequence of three relays, conventionally called *guard*, *middle*, and *exit*, and establishing a *circuit* through the sequence. The client encrypts a message once for each circuit relay (a process called *onion encryption*), sends it through the circuit, and each relay removes one layer of encryption before forwarding. The final relay sends unencrypted messages to the destination. The reverse process happens for messages from the destination to the

client. As a result of this process, the client identity is only directly observable in traffic between the client and the guard relay, and the destination identity is only directly observable in traffic between the exit relay and the destination.

In order to be real-time and efficient, Tor does not mix, pad, or delay traffic. Therefore, it is vulnerable to attacks based on traffic analysis. For example, an adversary that can observe a circuit between the client and guard and also between the exit and destination can correlate the traffic patterns and deanonymize the connection [8]. Thus entities that can observe parts the underlying network infrastructure, such as Internet Service Providers or Internet Exchanges, are a serious threat to Tor. Previous work has shown that individual autonomous systems and Internet exchanges are in fact frequently in a position to break Tor's security [15, 17, 22, 23, 30]. However, almost all of this analysis uses heuristic route-inference techniques whose accuracy may not be satisfactory. Murdoch and Zieliński [30] do study Tor security against IXes using traceroutes from Tor relays, but the traceroutes are performed from the UK only, and the analysis does not consider whether IX adversaries can be avoided during path selection.

2.2 Internet routing

Internet routing at the highest level is performed among autonomous systems using the Border Gateway Protocol (BGP) [32]. An AS is a network with an opaque internal routing policy (e.g., using OSPF [29], IS-IS [9], RIP [27], or iBGP [32]) that routes traffic to and from other networks. BGP is a *path-vector* routing protocol since neighboring networks advertise the whole AS path that they will use to send traffic to a given destination. A path is advertised for an IP *prefix* and represents the path used for all IP addresses sharing that prefix. Path-vector routing enables each AS to make complex routing decisions based on factors such as individual contracts with other ASes.

Understanding the behavior of such complex routing policies on the Internet is a challenging problem. Routers just propagate the routes that they provide for a given neighbor to use, and so different Internet vantage points reveal different subsets of global routing behavior. Sources of routing data include the Route Views Project,³ which provides BGP routing information from many large ASes, and CAIDA Archipelago,⁴ which provides and analyzes traceroute data from three teams of 17–18 monitors distributed worldwide. Gao describes how to use such data to infer AS-level Internet

¹ TorPS: <http://torps.github.io/>

² <https://metrics.torproject.org/>

³ <http://www.routeviews.org/>

⁴ <http://www.caida.org/projects/ark/>

routes [18]. Gao’s method uses heuristics to classify the observed connections between ASes by their economic relationship (viz. customer-to-provider, provider-to-customer, peer-to-peer, or sibling). Shortest-path valley-free routing is used to infer the route between two hosts. Valley-free routing verifies paths have all costly customer-to-provider links first with an optional sibling or peer-to-peer link followed by only preferred provider-to-customer links on the path. Qiu and Gao improve the accuracy of this technique by incorporating the observed advertised BGP paths [31]. In addition, they describe how to infer a set of possible paths rather than just one. Their results show that these techniques can infer the exact correct AS path for 60% of evaluation ASes; furthermore, the exact path is found within the top 5 predicted possible paths for 83% ASes and within the top 14 paths for 86% ASes.

Many links between ASes occur at Internet exchanges. These are facilities that provide space and infrastructure for ASes to locate routers and establish connections. Ager et al. [4] describe how the largest IXes may provide links among hundreds of ASes and carry petabytes of traffic per day. Augustin et al. [7] describe how IXes on Internet routes can be detected using traceroutes and an index of known IXes and their IP prefixes. They identify 44 000 peering relationships between ASes at IXes. Each peering between two ASes indicates that *some* traceroute passed directly from one AS to another through an IX. Discovering such links can improve the accuracy of AS path inference techniques. However, as we will observe, it doesn’t discern among different router-level paths taken between the same two ASes, which may pass through different IXes.

2.3 Traceroute measurement

The traceroute tool is extraordinarily useful in measuring routing behavior on the Internet. The basic algorithm iteratively issues UDP packets with unique ports and an increasing time-to-live (TTL) value. Then for any ICMP Time Exceeded response it uses the contained UDP port number to identify the TTL value used and infers that the source IP address is located at that path position. There are many variations of the basic algorithm [26] which provide different levels of success depending on the traffic engineering (e.g., filtering and load balancing) that occurs en route.

In addition to such problems with traceroute itself, it is not always straightforward to make inferences about Internet paths from a traceroute. For example, Mao et al. [28] describe the difficulties of inferring an AS-level path from traceroutes, which include that different iterations of a single traceroute might take different paths, that reported IP addresses may be from a network interface other than the one that actually re-

ceived it, and that mapping from IP address to AS number is non-trivial due to inaccurate WHOIS information. Augustin et al. [7] discuss similar issues in inferring the presence of IXes from traceroutes.

Nevertheless, traceroutes do provide a generally accurate picture of how packets are actually routed at the AS level. Research on AS-level routing rarely uses any real ground truth data because routing involves the proprietary information of many parties. Instead, traceroutes and advertised BGP paths are the most frequently used sources of data (e.g., [28, 31, 36]), although each has inaccuracies. A thorough comparison of these data [28] showed that among completed traceroutes (the type that we consider), approximately 90% of their AS paths matched the advertised BGP paths exactly.

Traceroutes serve as an important comparison point to AS-level path predictions. These *inferred* AS paths are much less consistent with advertised BGP paths, and in this paper, it is the inferred paths that we are trying to evaluate. Only 60% of AS paths inferred using the Qiu-Gao algorithm have an exact match with advertised BGP paths on average [31]. Indeed, Qiu and Gao justify their inference method over using traceroutes only because “traceroute requires the access to source machines and is resource consuming”.

Moreover, the mismatches that do exist between traceroutes and advertised BGP paths often favor traceroutes for Tor security analysis. Mao et al. [28] show that advertised paths miss exchange ASes, sibling ASes, and tail ASes. These ASes *should* be included when considering Tor security, and such mismatches are found in 1–3% of the completed paths they compare between traceroute AS paths and advertised BGP paths.

For IXP inference, traceroutes are the main data used in the literature (e.g., [7, 30]). Indeed, the IXP inferences methodology that we apply uses traceroute data as a primary data source.

3 Mapping Network Adversaries

3.1 Measuring Internet Paths

3.1.1 Generating Traceroutes

Our measurement study consists of running traceroutes from Tor relays to various destinations in the Internet. We use the *scamper*⁵ network tool, which probes multiple destinations in parallel, and uses techniques to accurately discover the Inter-

⁵ <http://www.caida.org/tools/measurement/scamper/>

net path traversed by packets in the presence of multi-path load balancing [6, 24].

For our measurements, we extracted the set of advertised destination IP prefixes from the September 2013 Routing Information Bases (RIBs) of the Route Views routers. Each relay running the measurements picks a random IP address within each of the approximately 500K prefixes and performs a traceroute to that destination. We also collected traceroutes to the Tor relays themselves as well as a scan of all /24 IPv4 subnets, but this data was not used for the analysis in this paper. We focus on the advertised prefixes to make the analysis more tractable. We expect addresses within a prefix to use the same or similar routes, and our analysis of CAIDA’s traceroutes to all /24 IPv4 subnets [3] found that 81% of the time traceroutes destined to the same routable prefix traversed the same set of ASes. Our measurement scripts are available for public review.⁶

3.1.2 Processing Traceroutes

We next process the traceroutes to determine which ASes and IXes an Internet path has traversed. First, we filter out traceroutes that do not successfully reach the destination. Note that because we use randomized destinations, in many cases the destination may not exist or may be down; indeed, only a small fraction (8%) of probes reaches their target. However, 49% reach the AS of the destination, as determined by the MaxMind GeoIP database [2].

We further find that 94% of the traceroutes are missing some hops from the path. In some cases, we believe missing paths are caused by routers close to the probe source rate limiting their ICMP responses. To address this, we perform *route stitching*, where gaps in a traceroute are filled by path segments observed in other traceroutes. For example, if we see a path “A B C D E” and another path “A B * D F,” where “*” denotes a missing hop, we can repair the second path by inferring that the third hop must have also been C in this case. To minimize inaccuracies introduced by this repair mechanism, we only consider path segments that originate from the same host, and which are contained within the same batch of 64K traceroutes, which typically occur within an hour or two of each other. We validated this approach on complete paths and found that stitching would have given us the correct AS path result 96% of the time.

We then compute the ASes corresponding to each IP in the path using the GeoIP database. Similar to Mao et al. [28], we consider the corresponding AS path complete if the tracer-

oute reached the AS of the destination and there are no missing hops in the path on the boundary between ASes. For example, an AS path “AS1 AS1 * AS1 AS2 AS3” is considered complete, because the missing hop is contained entirely within AS1, whereas “AS1 AS1 * AS2 AS3” is considered incomplete. Overall, 28% of the traceroutes yield a complete AS path. We discard the other traceroutes from our analysis. We also identify an IX as on the path if the path contains an IP address from the list of known IP addresses of IX points as outlined in the following section.

3.2 Inferring Path ASes and IXes

We are interested in comparing the AS and IX adversaries identified from traceroute data compared to AS and IX adversaries inferred from AS maps which are much easier to attain and maintain. We predict AS paths from source to destination using Gao’s algorithm [18] to classify relationships and Qiu and Gao’s algorithm [31] to infer the top k paths (for $k = 1$ to 5). While advances have been made in classifying AS link relationships [25], we find that, when available, Qiu and Gao’s method of matching RIB paths is more accurate than using graph based methods based solely on AS relationships [23]. It is known that AS relationships are difficult to classify especially at the highly interconnected core of the AS graph. Violations in the valley-free principle from advertised routes often indicate erroneous AS relationship classification especially through top-tier ASes. Therefore Qiu and Gao’s method of prepending advertised routes to complete paths yields accurate results even with incorrectly classified AS relationships at the core of the Internet. Since the prepended hops are almost entirely easily classified customer-to-provider hops at the bottom of the AS graph, improving the AS relationship classification of the top-level ASes does little to improve overall AS path prediction accuracy.

To predict the presence of IXes, we recreate the work of Augustin et al. [7]. We scraped Packet Clearing House⁷ and the Peering Database⁸ in February of 2014 creating a list of 732 Internet exchange points and their known prefixes. We parsed over 200 million traceroutes from February and March 2014 collected from both the CAIDA routed IPv4 database [3] and the iPlane project,⁹ and identified IXes in the traceroutes using the list of IXes and IP prefixes. This analysis revealed roughly 130 000 Internet exchange point peerings between pairs of ASes. Our number is roughly twice the number of

⁷ <http://www.pch.net>

⁸ <https://www.peeringdb.com>

⁹ <http://iplane.cs.washington.edu/>

⁶ https://bitbucket.org/anupam_das/traceroute-from-tor-relays

	Min	Max	Total
Traces	392 334	1 195 577	17 233 153
IP Reached	27 254	81 999	1 183 427
AS Reached	204 836	618 224	8 890 142
Repaired	26 375	876 386	9 643 679
Whole IP Path	0	16 694	253 058
Whole AS Path	11 285	397 533	5 350 713
Probed Hops	7 005 020	20 624 809	297 301 238
Responsive Hops	1 594 449	7 041 819	109 046 956
% Hops Responded	19	55	37
Inferred Paths	10 693	220 449	4 367 097

Table 1. Traceroute experiment statistics (28 hosts)

links found by Augustin et al. in 2009, which is unsurprising considering the trend for ASes to peer at IX points. This IX inference technique thus produces a list of inferred IXes between AS pairs, where each entry in the list consists of a source AS, a destination AS, and the set of IXes that were ever observed in a traceroute from the source AS to the destination AS. We use the list to identify potential IX points on AS-level paths throughout our experiment.

4 Measurement versus Inference

We first investigate how closely ASes and IXes identified through inference correspond to ASes and IXes measured with traceroute. We conduct analysis on 17 million traceroute measurements obtained from 28 Tor relay servers from January 19–26, 2014 as summarized in Table 1. Our 28 servers included many of the largest Tor relays and cover a portion of the Tor network which includes 23% of guard node capacity and 26% of exit node capacity. Thus, their measurements can give us good insight into how traffic is routed in and out of Tor. Of these 17 million traces, only about 1 million reached the target IP address with roughly 250 000 complete paths with no missing IP hops. We find that roughly 9 million paths can have some hops filled in by using the repair techniques presented in Section 3. We map each IP address to AS numbers using the MaxMind GeoLite ASN database taken from January 15th 2014 [2]. The AS-level paths are then parsed to remove routing loops, duplicate hops, and missing hops directly preceded by and followed by the same AS. After processing, we obtain 5.3 million complete AS-level routes.

4.1 Identifying AS Adversaries

We first investigate the accuracy of inferring ASes between an arbitrary source/destination AS compared to the ASes iden-

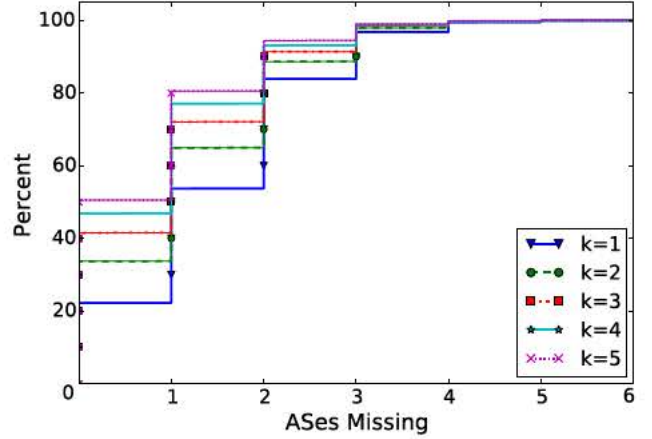


Fig. 1. CDF of Missing ASes over all Traces

tified in our collected traceroutes. The analysis of path prediction accuracy is conducted on traceroutes collected during January 19–26, 2014 giving 5.3 million traces contain 450 000 unique AS source and destination pairs. We divide the traceroute data into 24-hour windows. Routing table dumps are downloaded from each server from the Route Views project from the time closest to the 12th hour of the window. Each day window contains an average of 15 prefix table dumps with between four to six gigabytes of route information broadcasts. Using Qiu and Gao’s model we predict the top $k=5$ paths for roughly 400 000 of these pairs with the rest failing due to either the source or destination AS missing from the Route-Views routing tables. The 400 000 successful path inferences cover 4.5 million of our 5.3 million traces with AS paths. We consider the inference identifying the correct path if it matches the AS path seen in the traceroute for any of the top k paths considered.

Figure 1 is a CDF showing the number of ASes seen in the traceroute but missed by the top k predicted paths. Zero missing ASes correspond with a correct path prediction for at least one of the k paths. Using only the top path from the prediction, yields roughly 20% prediction accuracy with a decreasing return for higher levels of k and a maximum accuracy of 48% when considering the top 5 paths. This accuracy is far lower than the 83% accuracy for the top 5 paths attained by Qiu and Gao; however, their validation was conducted using Route Views data as the ground truth and not traceroute data [18]. We surmise the lower accuracy is due to a combination of known error sources both from the increase in prevalence of IX peering [4] and inherent errors in traceroute measurements from actual AS-level paths [36]. We finally note that the overall accuracy of prediction is similar to our extensive analysis of accuracy against CAIDA traceroutes demonstrating that the Tor network would benefit from improvements to path prediction in the general case [23].

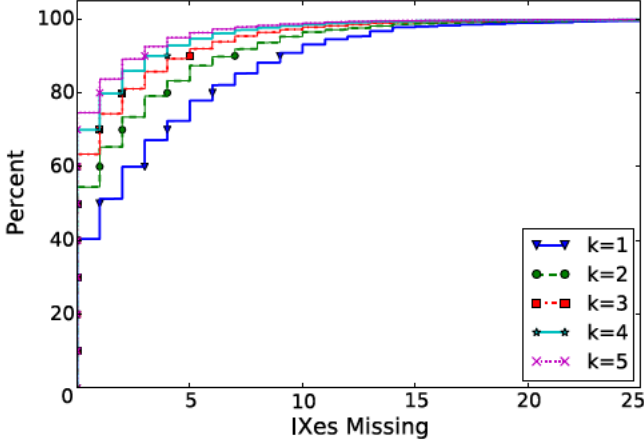


Fig. 2. CDF of Missing IXes over all Traces

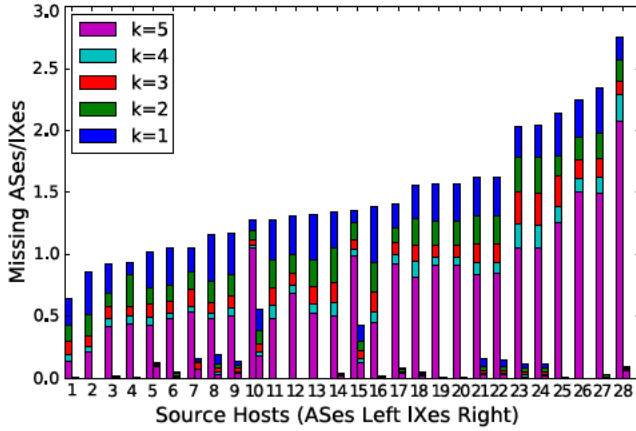


Fig. 4. Avg Missing ASes and IXes Per Host

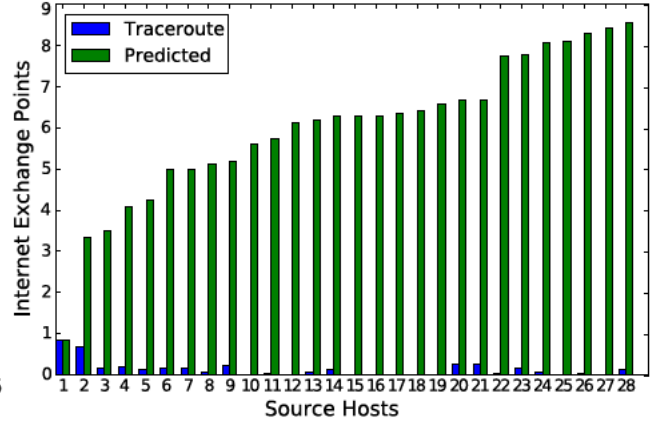


Fig. 3. Observed Internet Exchange Points

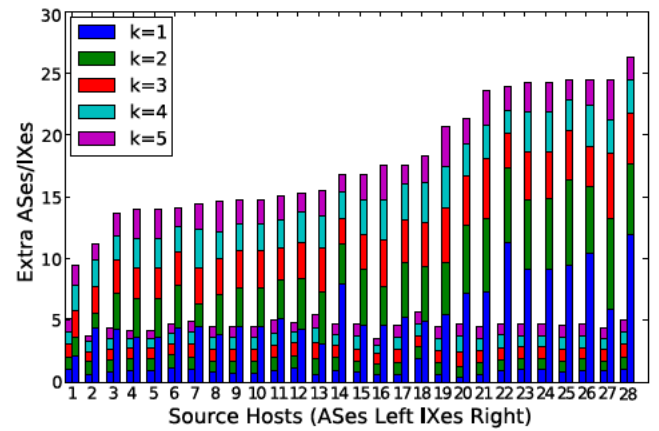


Fig. 5. Extra ASes and IXes Per Host

4.2 Identifying IX Adversaries

Given an AS path, we can identify the set of potential IXes that could occur on this path by considering which IXes can be used for each AS–AS hop, as discussed in Section 3.2. Figure 2 compares the set of potential IXes for the top k predicted AS paths to the set to the IXes identified by IP address prefix in traceroutes. Once again, a value of zero indicates that all IXes have been identified in the inference. We find that the top path identifies roughly 40% of the IXes and the top five paths identify roughly 74% of the IXes.

We expect traceroutes to provide a much more accurate picture of which IXes were involved on a path than AS path predictions. A pair of ASes will often have multiple peering points, depending on the geographic location the source and destination; as a result, only a fraction of traffic between the two ASes will use a given IX. In Figure 3, we compare the set of IXes on a traceroute to the predicted set of IXes that could be used at each AS–AS hop in the traceroute. We see that while most traceroutes do not traverse *any* IX, the AS–AS hops result in 3–8 potential IXes on average. This experiment

demonstrates the limitations of using only AS-level information to infer IXes on a path.

4.3 Choosing k Top Paths

Choosing the k top paths to consider when predicting AS and IX points presents an important tradeoff between missing ASes/IXes versus severely overstating the number of ASes/IXes on a given path. Figures 4 and 5 show the missing AS/IXes and extra AS/IXes seen by the path prediction algorithms for the k top paths from $k = 1$ to 5. For ASes, we see diminishing returns for missing ASes for larger values of k with false positives increasing quickly for larger values of k . Overall, the average attainable missing AS accuracy is close to 1 for the top path decreasing down to 0.6 for the top 5 paths.

We compare the IXes found using vulnerable AS–AS hops from the inferred AS paths directly to the IXes identified by prefix in the traceroutes. In general, very few IX points were seen in the traceroutes. In most hosts, IX identification is helped very little by increasing the top paths with the average

missing IX of about 0.2 per hop. This result is unsurprising because if there are no IX points in the traceroutes, then there can be no missing IXes in the inference. Unfortunately, the false positives for IX points are problematic with linearly increasing averages ranging from 10–25 for each of our hosts illustrating the need for better methods in identifying IX points.

For AS adversaries, a k value of 1 or 2 seems most appropriate to identify most AS adversaries without causing too many false positives. Higher values of k give lower rates of return while causing a linear increase in false positives. Identifying IX adversaries is much more problematic. Since the traceroutes identify very few IX adversaries to begin with, a k value of 1 appears to work well. The inaccuracy of the method can be seen in the false positives which also increase linearly with k but greatly over-predict the number of adversaries even with a k value of 1. The inaccuracy of AS and highly inaccurate IX prediction could potentially cause serious problems when designing a system of AS/IX independence in Tor. We analyze the effects of this inaccuracy in the following sections.

5 AS and IX Adversaries in Tor

Errors in path prediction call into question previous work that has used path prediction to both evaluate the security of Tor and propose changes to Tor’s path selection based on path predictions. Understanding the effect of the errors uncovered by our traceroute measurements requires taking into account the specific properties of Tor.

We accomplish such an analysis by simulating the Tor protocol and network at a high level. We use and adapt the Tor Path Simulator (TorPS)¹⁰ to perform Monte Carlo simulation of Tor path selection by a single client. By using the hourly network “consensuses” and server “descriptors” archived by CollecTor,¹¹ we can recreate the state of the Tor network over the period we run our simulations, including features such as the number, bandwidths, and addresses of Tor relays available in any given hour. We simulate “typical” user activity using the recorded volunteer trace of Johnson et al. [22], which includes user behaviors such as web search and webmail on a plausible daily schedule. Over the course of a week, this schedule results in 2632 *streams* (i.e., TCP connections over Tor), each to one of 205 distinct IP addresses occupying 168 unique ASes, on either port 80 or 443. Finally, we run simulations using the most common client ASes as measured by Juen in Fall 2011 [23].

Simulating path selection in Tor allows us to estimate which Internet hosts a user’s traffic is likely to flow over in a typical use case. Then we can use our traceroute data to determine the specific Internet routes that traffic would take and evaluate the resulting security. Specifically, we provide new estimates for how often a Tor stream flows through the same AS or IX between the client and the guard and between the destination and the exit. When this happens, the AS or IX is in a position to deanonymize the client. This issue was previously studied only using inferred AS paths and IX sets.

In addition, using this method we provide an improved evaluation of the repeatedly-proposed [15, 17] modification to Tor to use AS/IX path inference to choose relays that are *path independent*, that is, that result in paths for which the same AS or IX cannot observe both the client and the destination. We modify TorPS to produce the first simulator for path-independent Tor (to our knowledge) that reproduces how path selection occurs over time, including features that have the potential to significantly alter the effectiveness of the path-independence requirement, such as guard lists and circuit reuse. We apply our traceroute measurements to the results of these simulations to evaluate the effectiveness of path inference as a basis for path independence in Tor.

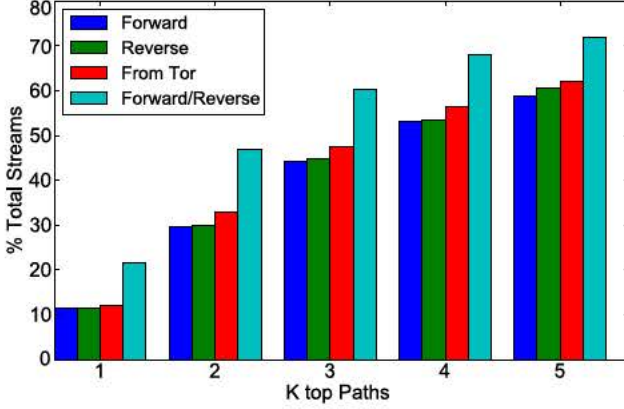
5.1 Vanilla Tor

All of our Tor simulations run over the week of January 19–25, 2014. When producing and analyzing these simulations, we generally use the same data sources and inference algorithms as in Section 3.2 to produce AS path inferences, AS-level IX inferences, and traceroute IX inferences. We use daily AS-path inferences conducted from January 19–25, 2014 compared to the traces from each day of the simulation week. We also use the daily Route Views prefix-to-AS datasets to determine routed prefixes and to map IPs to ASes. When analyzing our simulations using traceroutes, we use all of the traceroute measurements gathered during the week of January 19–25, 2014. In our analysis we match a traceroute to a pair of communicating hosts in Tor if the source prefix and destination prefix match.

We first conduct a simulation using the default Tor path selection algorithm. We consider clients coming from 50 of the top 200 most common client ASes (as measured by Juen [23]). Each AS advertises hundreds of possible prefixes in the Route Views data. We select at random twenty prefixes per client AS for a total of 1 000 client prefixes for the simulations. The simulator runs 10 000 repetitions of simulated traffic using input data from the week of January 19th–25th 2014 yielding over 24 million traffic streams per client prefix with 18.2 million unique streams. We identify the presence of AS and IX adver-

¹⁰ <https://github.com/torps>

¹¹ <https://collector.torproject.org/>

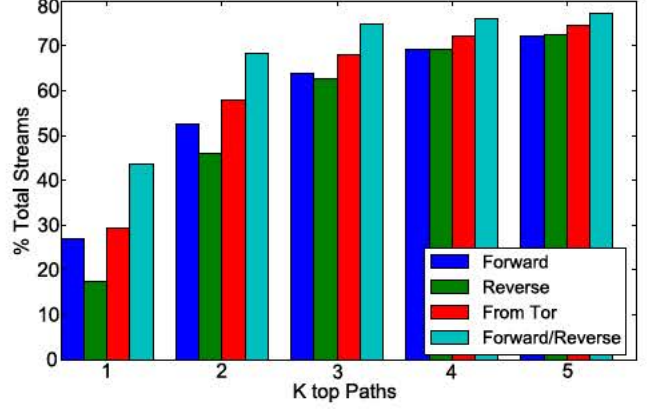
Fig. 6. Directional AS Compromises for k Top Paths

saries using AS-path inference with the top k paths ($k=1$ to 5) and our collected traceroute data from January 19–January 25. In total, we have inferred path information for an average of 18 million streams per client prefix (18 billion total) and traceroute information for an average of 112 000 streams per client prefix (14 million total).

5.1.1 Inferred Adversaries

We first look at the percentage of simulated Tor paths which have the same AS or IX on both the client-to-guard path and the exit-to-destination path using only the inferred paths. We look at the percentage of compromised paths considering the set of ASes and IXes in the forward direction (client to destination), the reverse direction, and the forward and reverse directions combined. We also consider the direction of streams leaving Tor; i.e., from the guard to the client and from the exit to the destination. This direction matches the direction of our traceroute measurements from Tor relays to external IP prefixes and allows us to compare the predicted paths with traceroute data, without errors being introduced due to asymmetric Internet paths that traverse a different set of ASes and IXes. We call this path the Tor path.

Figures 6 and 7 show the percentage of inferred ASes and IXes for each direction and top k paths averaged over all 18 billion inferred streams. Considering only the top path, we see 11.6%, 11.6%, 12.1% and 21.6% AS compromise rates for the forward, reverse, Tor, and forward/reverse paths respectively. We see a significant increase in AS adversaries when considering more paths topping at 58.8%, 60.6%, 62.0%, and 71.8% when considering the top 5 paths for the forward, reverse, Tor and forward/reverse paths respectively. We notice little difference between the compromise rates of the Tor paths versus the forward or reverse. As expected, the forward and reverse

Fig. 7. Directional IX Compromises for k Top Paths

combined represents a higher inferred compromise rate since we consider two sets of ASes per path. The forward/reverse has roughly a 10% greater rate of compromise for the top path and roughly a 20% greater compromise rate when k is varied from 2 to 5. For the top path, the IX compromise rates were higher with 27.0%, 17.5%, 29.3% and 43.5% for the forward, reverse, Tor and forward/reverse paths respectively. These increased rapidly at first leveling off to 72.3%, 72.5%, 74.7% and 77.2% for the top 5 paths. Once again, the forward/reverse paths contain more potential IX adversaries due to considering more paths. There is little significant difference between the compromise rates of the forward paths and the Tor paths. We also note that the number of inferred potential adversaries greatly increases when considering a higher number of top k paths.

5.1.2 Measured and Inferred Adversaries

We now compare the inferred AS and IX adversaries to the AS and IX adversaries actually present in the traceroute measurements for all of our simulated Tor circuits. To make the comparison fair, we only consider the traceroutes and inferred paths going from the Tor guard to the client and from the Tor exit to the destination. As seen in the last section, the inferred paths using the Tor direction contains similar compromise rates to the paths in the forward and reverse directions. We thus consider the subset of paths for which we have both AS inferences and measured traceroutes in the Tor direction giving us a set of 141 million streams from 1000 unique client prefixes.

Figure 8 shows the CDF of streams compromised in the traceroute measurements compared to the inferred for various k top paths. Interestingly, the AS compromise rates for the top path is similar to the actual compromise rates seen in the mea-

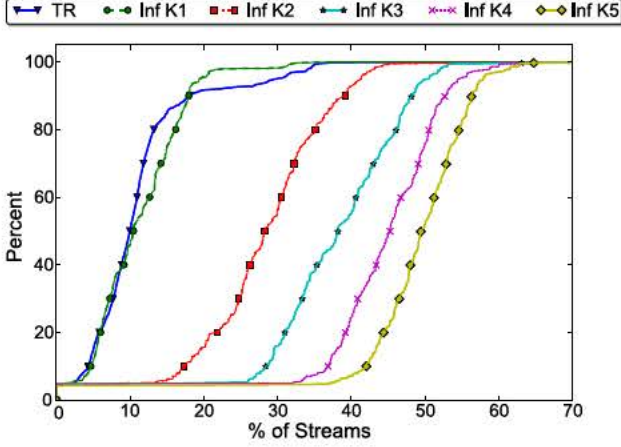


Fig. 8. AS Compromises Measured and Inferred

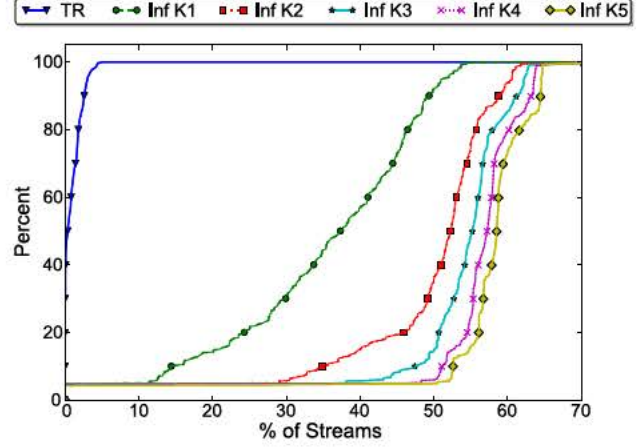


Fig. 9. IX Compromises Measured and Inferred

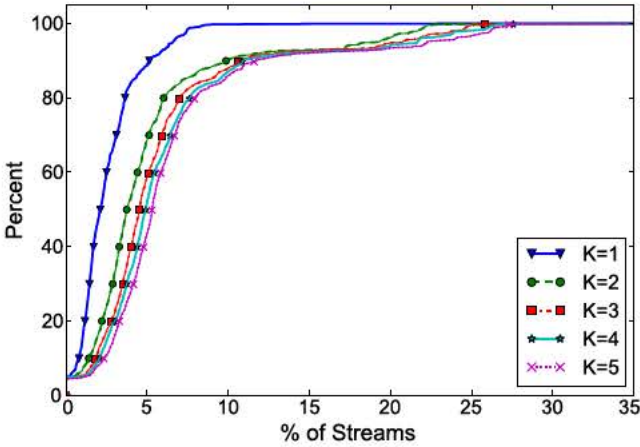


Fig. 10. AS Compromise Agreement

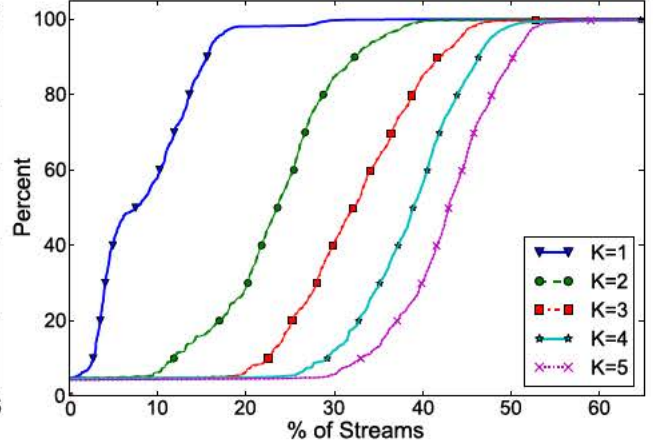


Fig. 11. AS Compromise False Positives

surements. Considering the top 2 paths more than doubles the inferred compromise rate with lower increases with increasing k topping out at a little under a 50% compromise rate for half the paths. Figure 9 shows the CDF of streams compromised with measured versus inferred IX adversaries. The actual percentage of paths with an IX adversary identified by prefix is much smaller than the inferred value with only 0.8% of streams seeing an IX adversary on both the client to guard and exit to destination simultaneously. The inferred paths greatly over exaggerate the threat with the top path giving an average of 40% compromise rate and the top 5 five paths giving an average of nearly 60% compromise rate. Thus, the method of inferring IX adversaries greatly over predicts the number of actual IXes seen when measuring paths using traceroute.

We now consider the differences between adversaries seen using the inference methods versus the adversaries seen in the traceroutes. We consider adversaries seen in the inferred set but not in the measured set as false positives and adversaries seen in the measurements but not the inferred set false nega-

tives. While the traceroute measurement can contain errors and does not constitute perfect ground truth, we consider it more reliable than the inferred methods. In the following analysis all percentages are the percentage of paths compared to the set of all 141 million simulated paths for which we have both inferred and measured data.

Figures 10 through 15 show the CDFs for the percentage of streams compromised per prefix for both ASes and IXes that both methods agree, the inference indicates an adversary while the measurement does not (false positives) and the measurement indicates an adversary while the inference does not (false negative). We see that while the percentage of overall AS compromises for the top path was similar in the last section, they do not agree on which AS is causing the compromise. In our measurements, we find roughly 10.9% of streams could contain a potential AS adversary. Unfortunately, the measured and inferred AS only agree for an average of 2.6% AS compromises when considering the top path. Increasing to the top two paths improves agreement by a factor of 2 to 5.1% aver-

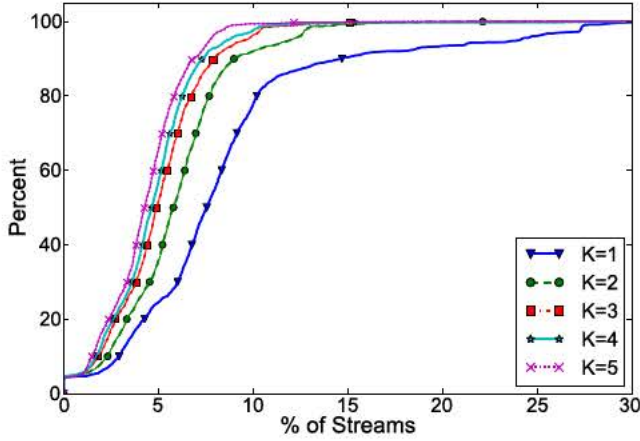


Fig. 12. AS Compromise False Negatives

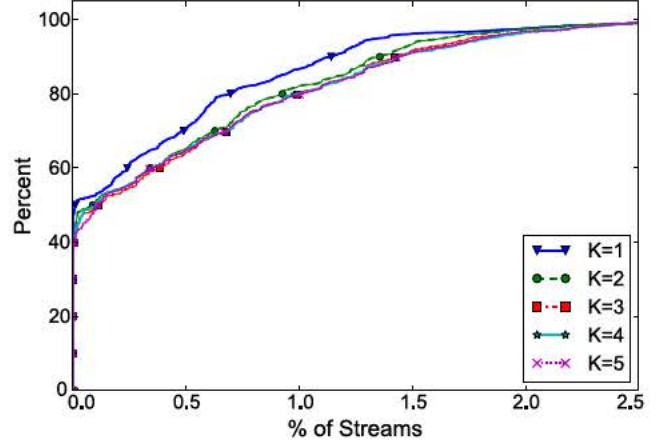


Fig. 13. IX Compromise Agreement

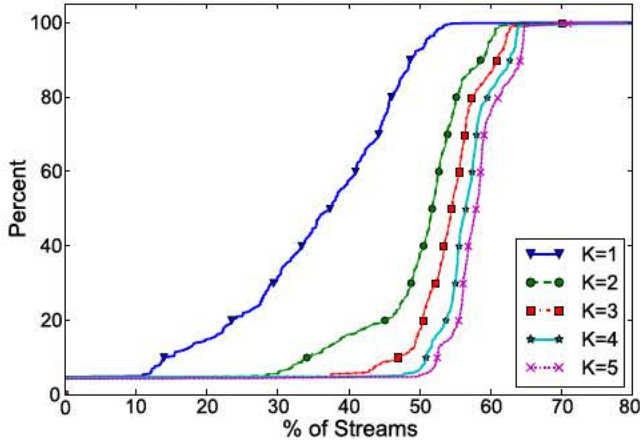


Fig. 14. IX Compromise False Positives

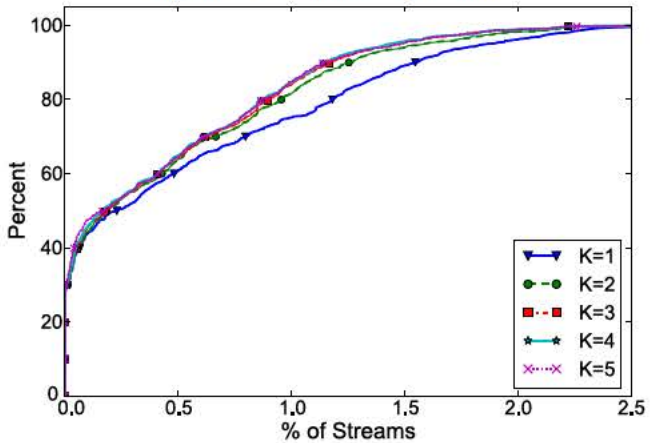


Fig. 15. IX Compromise False Negatives

age agreement with higher k values giving diminishing returns after that. Unfortunately, increasing k from 1 to 2 significantly increases the average number of false positives from 8.5% to 22.6% with a more linear increase with k up to 41.1% with $k = 5$. For false negatives, the greatest drop once again occurs when going from the top paths to the top two paths from 8.4% to 5.8% with diminishing returns with increasing k and a minimum of 4.3% average with $k = 5$. Overall, the AS inference with the top 2 paths catch a little less than half the measured AS adversaries catching 5.1% and missing 5.8% of the actually measured 10.9% of measured AS adversaries. Unfortunately, it still pre-emptively would eliminate 22.6% of paths which had no measured adversary.

The agreement with the IX adversaries is even lower. Both methods agree on only 0.36% of paths having an IX adversary considering the top path increasing to 0.44% for the top two paths up to 0.47% for the top 5 paths. The false positive rate is unacceptably high with 34.5% for the top path and 48.1% for the top 2 paths up to 55.7% for the top 5 paths. The false negative rate is 0.54% for the top path lowering to 0.45% for the top

two paths down to .42% for the top five paths. Thus eliminating paths based on the inference with the top path would catch 40.0% of the observed IX adversaries (0.9% of total paths) while eliminating 34.5% of paths unnecessarily. Using the top 2 paths would catch 48.9% of observed IX adversaries while eliminating 48.1% of paths unnecessarily. Thus, roughly half of all potential paths would be eliminated to catch the 0.9% of total paths with an observed IX adversary. These results motivate the need for better methods of inferring IX adversaries in order to effectively mitigate the threat to the Tor system.

5.2 Path-independent Tor

In order to avoid deanonymization by an AS or IX, Tor clients could attempt to choose Tor relays such that the forward and reverse paths between the client and guard are independent of the forward and reverse paths between the exit and destination, in terms of the ASes and IXes that appear. However, it is non-trivial to design a system that allows the client to do

(a) Undetected compromise among streams that successfully connected

	Top 1 Path	Top 3 Paths
Mean fraction of streams that have traceroutes	0.0037	0.0026
Mean fraction of streams with traceroutes that are w/o independence	0.0043	0.0014
Min prob of at least one stream w/o independence	0.018	0
Mean prob of at least one stream w/o independence	0.11	0.053
Max prob of at least one stream w/o independence	0.22	0.18

(b) Unnecessary failure among streams without any independent path

	Top 1 Path	Top 3 Paths
Mean fraction of all streams that fail due to independence constraint	0.051	0.060
Mean fraction of streams that have traceroutes	0.19	0.19
Mean fraction of streams w/ traceroutes that have an independent path	0.96	0.95
Min prob of at least one stream failure	1	1

Table 2. Path-independent Tor traceroute analysis over 189 top client ASes

so, because he must preserve his anonymity while making this decision, and Tor should be usable even by users with little bandwidth and low-powered devices.

As we discuss in Section 6, Edman and Syverson [15] presented the first detailed proposal for solving this problem with a system that provides enough data for clients to build an AS Internet map on which to run AS-path inference. They propose a slightly *less* accurate algorithm than Qiu and Gao’s for efficiency. Juen added IX inference to this idea [23]. None of the previous work explains how AS/IX-independent circuits should be created *over time*, and thus does not consider how path independence interacts with Tor guards or circuit reuse. Tor guards in particular are a key Tor feature that defends against malicious observation and deanonymization [16, 22]. Thus the prior work does not give a clear idea of how well AS/IX-independent path selection would work even if path-inference techniques were very accurate.

The inaccuracy of path-inference techniques is likely to negatively impact AS/IX-independent path selection in at least two ways: (i) missing an AS or IX on a path could cause the user to create a path vulnerable to deanonymization, and (ii) incorrectly believing that an AS or IX exists on a path could leave the user with few or no ways to connect to the destination. These problems are placed in tension by the inference methodology because false negatives make (i) worse and false positives make (ii) worse. For example, as the number k of top paths used in inference increases, false negatives should go down but false positives should go up. Moreover, the inference needs to have few false negatives on all paths *collectively*, or a user will face an increasing risk of deanonymization as he visits new destinations and is forced by network churn to use different relays. Similarly, an increasing number of false positives over time could force the user to choose between not con-

necting to certain destinations and exposing himself to more and more potentially-malicious guards.

We investigate the suitability of path inference as a basis for AS/IX-independent path selection using path simulation and our traceroute data, similar to how they were used in Section 5.1 to explore vanilla Tor security. As a byproduct of our research, we also expose a security-performance trade-off inherent in the path-independent approach and reveal some opportunities to fill in and improve past proposals.

5.2.1 Methodology

In order to evaluate AS/IX-independent path selection via simulation, we must fill in the details of the algorithm sketched out by prior work. We adapt the existing Tor path-selection algorithm for this purpose. We require clients to have at least 3 guards in their guard list and to have at least 2 guards active with AS/IX path information with the client when creating a new circuit. Upon receiving a stream request, existing circuits are examined for suitability, including path independence. If none is suitable, then circuit-creation is initiated by choosing an existing guard, then an exit, and then a middle. If a path-independent exit cannot be found for a given guard, the other guards are considered, and so on. If no exit is found for any current guard, then the circuit creation fails. We note that to enable a direct comparison with our traceroute data, our simulator only compares the inferred AS/IX path from the guard to the client and from the exit to the destination when determining path independence (i.e. only reverse entry and forward exit paths are used).

We generally follow the same experimental methodology as that followed in Section 5.1. We will not be estimating full distributions, and thus we use only 500 samples per client AS,

but we run experiments with the 189 of the top 200 client ASes that were in our AS-level routing map.

In our experimental analysis, we are able to use traceroute data to identify false negatives and false positives. 50 client IPs are chosen randomly from the set of the initial IPs in each prefix advertised by the client's AS (according to the Route-Views prefix-to-AS file that appears most recently before that stream occurred). To identify false negatives, we test streams that were successfully assigned to a circuit by looking for a traceroute from the guard's routing prefix to the client's and from the exit's prefix to the destination's. When both traceroutes are found, we look for ASes or IXes that appear in common. To identify false positives, we test streams that failed to connect by looking for a traceroute from any of the active guards at that time to the client and from any potential exit to the destination. If such a pair exists, we look for the lack of any AS or IX in common.

5.2.2 Results

Table 1a provides estimates for the effects of path inference errors on the security of path-independent Tor. The min, mean, and max values are taken over 188 top client ASes (we further excluded one that didn't advertise any prefixes during the simulation week). Our traceroute data provided path information (i.e. matched both guard-client and exit-destination host-prefix pairs in the direction out from Tor) for 0.26–0.38% of the simulations' streams (depending on whether the top 1 or the top 3 inferred paths were used to determine independence). Of these, between 0.14% and 0.43% were revealed to violate path independence. While compromise rates may seem acceptably low, even one Tor deanonymization is potentially serious, and over the course of the simulated week, a client had on average between a 5.3% and a 11% probability of experiencing at least one path-independence violation. In the most unlucky client ASes, path independence was violated with a probability as high as 18–21%!

Table 1b shows that this insecurity cannot simply be handled by increasing the number of top possible paths from which the inferred ASes and IXes are taken. It reveals that by increasing the number of top paths used in inference from 1 to 3, the fraction of streams for which no path-independent Tor circuit could be created increased from 5.1% to 6%. For these streams, no AS/IX path-independent exit could be found using any of the client's guards. Note that a stream failure of any kind *never* occurred in simulation with Tor's default path selection, because Tor doesn't require path independence, and many exits are available for each stream in the user trace. Such failures are particularly bad because the stream will not succeed until the Tor relay population changes sufficiently, a process which

could take days or weeks. Thus even a 5.1–6.0% failure rate has a severely deleterious effect on Tor's suitability for general Internet use. Moreover, we can see that every simulated client experienced at least one stream failure (i.e. the estimated failure probability is 1.0 for all client ASes).

However, our traceroute measurements offer the hopeful news for this problem that most of these stream failures may have been unnecessary. We were able to match a traceroute guard-to-client and exit-to-destination for 19% of failed streams. Our coverage of failed streams is so much higher than for connected streams because we look for a traceroute from any active guard of the client at the time and from any exit that could be chosen with that guard and for that destination (ignoring only the path-independence constraint). Among streams for which we were able to match at least one pair of traceroutes, 95–96% had a guard and exit that the traceroutes show would have been AS/IX-independent. In fact, this high false-positive rate is not just a result of having many exit paths about which to be incorrect, an average of about 80% of all guard and exit pairs with matched outgoing traceroutes were observed to be path-independent for both experiments.

5.2.3 Discussion

Our evaluation of AS/IX-independent path selection is not intended to make any definitive claims about its usefulness. Instead, we attempt to make reasonable choices about the algorithm details in order to get some idea of how well it might work overall and especially in conjunction with path-inference techniques. Indeed, there are many plausible improvements to the algorithm we have evaluated, such as choosing guards with different network locations to minimize the chance of stream failure, or perhaps allowing streams to use potentially unsafe circuits but limiting the number of potential observing ASes and IXes. Designing network-aware path-selection algorithms for Tor remains an open challenge with unsolved vulnerabilities such as adversarial relay placement [5] and path fingerprinting [12, 21].

6 Related Work

The threat to the Tor network for ASes to correlate traffic was first investigated by Feamster and Dingledine [17]. Using a simplified AS model with shortest paths they determined roughly 10–30% of circuits could be vulnerable to an AS adversary. Edmond and Syverson furthered the understanding of AS adversaries against the Tor network [15]. Using Qiu and Gao's AS path prediction model and an updated model

Method	Forward	Reverse	Both
Feamster and Dingleline [17]	17.7%	16.1%	NA
Edmond and Syverson [15]	10.9%	11.1%	17.8%
Wacek et al. [35]	NA	NA	27.4%
Juen [23]	7.1%	7.2%	11.2%
Current Work	11.6%	12.1%	21.6%

Table 3. Inferred AS Compromise Comparison (Top Path)

for the Tor network, they determined each circuit had an 11–18% chance that some AS adversary could compromise the circuit. They also presented a technique to choose paths without AS adversaries by using “Snapshots” of the AS topology. Akhoondi et al. presented LastTor, an optimization to Tor path selection to minimize latency by considering geographic location [5]. They propose using the set of k top most likely AS paths to eliminate AS adversaries. They do not report overall chances for any given AS to compromise a circuit. Recently, Wacek et al. studied Tor’s path selection algorithm [35]. They find that using the iPlane’s Nano AS map, Tor paths have a 27.39% chance to be vulnerable to an AS adversary. Vanbever et al. consider the threat of AS adversaries that actively manipulate BGP routing, showing that they can dramatically increase the chances of deanonymizing a Tor user over a period of time [34].

The danger of IX adversaries was first demonstrated by Murdoch and Zielinski who demonstrated that an IX could use a Bayesian approach to sample traffic and correlate Tor flows across ASes peering at the IX [30]. Juen further investigated the threat of AS and IX adversaries using Qiu and Gao’s AS model and the top k paths estimating the chance of any AS being able to compromise the circuit ranging from 10% to 42% [23]. He reports the chance of an IX compromise to be between 1% and 20%. Johnson et al. investigate the amount of time required for an AS, IX, or IX organization to compromise a circuit using Torps to simulate realistic Tor traffic [22]. They only consider the top 3 AS and IX adversaries as seen in their inferred data and report the overall chance of an AS compromise to be 1.6% for their top 3 ASes.

We now compare our results with the compromise rates of Tor streams against previous work. We calculate the percentage of Tor streams which contain an AS on the client to guard and exit to destination paths in the forward, reverse and forward and reverse directions for each of our 18 billion calculated streams. We then compare the results of our directional AS path inferences directly to the results from previous work and confirm that our AS path inferences give similar results for the top AS path as shown in Table 3. We find our results most closely correlate with the work of Edmond and Syverson with Juen’s results being lower than the average and Wacek et

al. being much higher. We find this result unsurprising since we also use the AS inference algorithm from Qiu and Gao. We surmise that the AS inference from iPlanes produce higher compromise estimates as seen in Feamster and Dingleline and Wacek et al. Juen also uses a modified AS mapping algorithm which may produce lower compromise rates.

Johnson et al. investigated the time expected before a user would most likely use a stream compromised by an AS or IX adversary. Since we only have inferred and traceroute data for 0.8% of streams, it is not possible to directly compare the time to compromise for our clients. Instead, we investigate the ability of the top 3 AS and IX adversaries to compromise a Tor stream. Once again, we only consider streams which we have both inferred and traceroute data. The ASes and IXes with the highest probability to compromise a Tor stream are shown in Table 4. Interestingly, we observe the same set of three top AS adversaries but in a slightly different order. We also see the top IX adversary as number 2 for compromise rates. We see a similar 0.5% rate of AS streams compromised by our top AS adversaries. We see a higher rate of overall streams compromised by our top IX adversary at 0.4% compared to roughly 0.1% in Johnson’s work. The overall compromise rates of all streams using the traceroute measurements is much more interesting. The traceroute measurements never see AS6939, the top compromising AS in the inferences. On the other hand, the traceroute measurements indicate AS1299 can compromise the same percentage of streams as indicated in the inference. We see drops for both top IX compromise rates for the measurements versus the inferences. Once again, Equinix Ashburn is not observed in the traceroute measurements.

Overall, we expect a drop in the actual ability of an IX point to compromise a Tor stream primarily due to the extremely high false inference of IX points. The difference between AS compromise rates shows that the path inference was always wrong in identifying AS6939 when compared to traceroutes; however, AS 1299 was seen in the traceroutes at similar rates as predicted. Thus, the inference accuracy appears to vary greatly depending on which AS is being considered as an adversary.

7 Limitations and Future Work

The data in this study is limited in several ways. While our volunteer measuring relays covered roughly 25% of Tor selection probability at the AS level, it still only contains 28 hosts. In addition, all path inferences were done on paths from Tor relays, leaving us without symmetric path information. Furthermore, we collected most of our data in the span of weeks, and so missed alternative routing paths and routing instabilities. We

AS	Our Rank	Johnson et al. Rank	Johnson et al. Comp %	Comp %	TR Comp %
AS6939 HURRICANE Electric	1	3	0.6%	0.4%	0.0%
AS3356 Level 3 Communications	2	1	0.4%	0.5%	0.13%
AS1299 TeliaNet Global	3	2	0.4%	0.5%	0.5 %
IX	Our Rank	Johnson et al. Rank	Johnson et al. Comp %	Comp %	TR Comp %
LINX Juniper	1	NA	NA	0.4%	0.05%
DE-CIX Frankfurt	2	1	0.1 %	0.4%	0.05%
Equinix Ashburn	3	NA	NA	0.4%	0.0%

Table 4. Stream Compromise Rates for the Top 3 AS and IX Adversaries for our Work compared to Johnson et al. [22]

also lack ground truth because of measurement weaknesses such as missing or incorrect traceroute hops, missing or stale IP prefix announcements from the public route collectors, and incomplete or incorrect IX prefix data. We look forward to the opportunity to expand network measurement in cooperation with Tor and using third-party vantage points such as Looking Glass servers. We also hope to make use of advances in measurement tools to advance this line of inquiry.

A problem posed by our results is to design solutions for Tor to more accurately assess network routing and use that to improve security. One promising approach is for Tor to adopt the measurement techniques that we used in this study and regularly perform traceroute measurements from each of its relays. Our experience shows that it is feasible to do so and cover the IPv4 address space at the prefix and even /24 subnet level.

Evaluating the effectiveness of using measurements to detect AS and IX adversaries requires an understanding of the characteristics of internet paths. It is important to understand how often internet paths between a given set of hosts change in order to update measurements and alert clients to potential adversaries. It is also important to understand what prefixes can be aggregated when measuring paths. Previous work has stated that between 66–83% of internet paths are stable over the course of a 24-hour period [37].

While our measurements were not designed to track paths over time, we do have enough measurements that we can observe the stability of repeated measurements to the same destination /24 prefix. Table 5 shows the number of pairs of paths, percentage of identical paths and average number of missed ASes and IXes on differing paths for various windows of time between measurement. While the numbers of collected traceroutes are too small to make final conclusions, we do see only 19.9% of paths stable in measurements taken within two hours. This result must be further investigated since the number of divergent paths contain both a time delay and a different destination IP address within the same /24. Thus, we have error both from differences in target addresses and potential routing changes between measurements.

As expected, we do see lower rates of identical paths when increasing the time between measurements; however, we do not see much difference in the number of extra ASes and IXes introduced when measuring a different path. We can expect to have between one to two different ASes when conducting the second measurement and roughly 0.01 missed IX point. The relatively low number of measurements with identical paths will require further study into path variability. Since these questions can only be answered by a larger set of measurements from Tor operators conducted over a longer period of time, we leave this larger, more ambitious study as important future work. However, we optimistically note that recent work has shown promise in predicting what subset of Internet paths change often and presented novel methods to estimate the rate of change to keep measurements current [10, 11, 20]. We believe such work shows the potential in a measurement based countermeasure to AS and IX adversaries, but leave the specifics of the design and validation to future work.

Another remaining challenge is to move past the current focus on AS-level techniques and adversaries. As Jagard et al. describe [19], an adversary may find it easier to control a group of IP routers running a certain version of software than to observe those in the same AS or IX. An adversary may also combine strategies and both observe the Internet at certain locations and run relays in selected other locations. Evaluating the threat of more complicated and realistic network adversaries will require both better adversary modeling and more detailed route inference techniques.

8 Conclusions

We have presented a measurement study to evaluate the suitability of Internet AS and IX path-prediction algorithms to assess and mitigate the threats from network-level adversaries to the Tor network. Using traceroute data from the volunteer operators of 28 Tor relays, we show that current techniques for inferring AS-level Internet paths and the IXes on them signifi-

Period	Measurements	% Identical	Average Missed ASes	Average Missed IXes
2 Hours	128	19.9	1.7	0.01
12 Hours	474	17.2	1.6	0.005
1 Day	826	18.7	1.7	0.01
3 Days	2572	16.6	1.6	0.01
7 Days	13340	14.9	1.6	0.01
28 Days	19668	10.1	1.6	0.007

Table 5. Repeated Path Measurements over Time

cantly overestimate number of ASes and IXes traversed by Tor traffic.

To evaluate how our results affect the current and future security of Tor, we perform Monte Carlo simulations of Tor’s current path-selection algorithm and the AS/IX-independent path-selection algorithm proposed in the literature. When we examine the results, we see evidence that Tor is likely less vulnerable to an AS or IX adversary than has been previously found. A direct comparison with a prior evaluation shows that it is likely to have overstated the risk of a single AS many times over and that of a single IX by an order of magnitude.

We also find that the AS/IX-independent path-selection algorithm may still leave a significant chance for users to be deanonymized over time due to the errors in path prediction — we estimate a 5–11% risk in just one week when the claimed chance is 0%. Moreover, we find that this algorithm appears to force a tradeoff between connection failures and exposing users to potentially-malicious relays, even though in nearly all cases the failures could be avoided with better measurement.

Our results suggest the importance of accurate measurement both for understanding Tor security and for improving it.

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Appendix

Details of Participating Tor Relays

Traceroutes from our 28 participating Tor relays originated in 14 different countries. Table 6 summarizes the guard and exit probabilities of the participating relays in the Tor network at the relay, AS, and prefix level. The guard and exit probabilities for all relays are taken from the Tor consensus of January 19, 2014 (at 12am) obtained from CollecTor [1]. Guards are taken to be relays with the following flags in the consensus: Running, Valid, Guard, and Fast. Exits are taken to be relays with the Running and Valid flags, without the BadExit flag, and with an exit policy that doesn't reject all ports and IP addresses. Relay ASes and prefixes are determined using the Route Views prefix-to-AS mapping of January 19, 2014 obtained from CAIDA¹² and longest prefix match on that same data. The guard (exit) probability for an AS or prefix is calculated as the sum of guard-selection (resp. exit-selection) probabilities of all relays contained in that AS or with a longest prefix match.

¹² <http://www.caida.org/data/routing/routeviews-prefix2as.xml>

IP	Country	AS Number	Relay Probability		AS Probability		Prefix Probability	
			Guard	Exit	Guard	Exit	Guard	Exit
81.7.13.84	Germany	35366	0.14%	0%	1.66%	0.37%	1.4%	0.27%
81.7.11.129	Germany		0.24%	0%				
37.200.98.5	Germany	34011	0.36%	0%	2.29%	0.048%	0.63%	0.028%
213.185.88.234	Germany	29354	0.19%	0%	0.19%	0%	0.19%	0%
185.15.244.124	Germany	24961	0.22%	0%	2.02%	3.39%	0.23%	0%
134.255.239.61	Germany	197071	0.09%	0%	0.10%	0%	0.09%	0%
23.239.134.29	United States	33182	0.03%	0%	0.05%	0%	0.034%	0%
206.217.135.164	United States	36352	0.07%	0%	0.89%	0.23%	0.12%	0%
192.3.142.234	United States		0.14%	0%			0.14%	0%
216.230.230.247	United States	40156	0.14%	0%	0.15%	0%	0.14%	0%
23.92.65.25	United States	54540	0%	0%	0.089%	0%	0%	0%
109.232.224.91	Netherlands	57172	0%	0%	0%	0%	0%	0%
146.185.143.144	Netherlands	46652	0.0002%	0.002%	0.90%	0.54%	0.24%	0.037%
88.191.162.192	France	12322	0.1%	0%	1.26%	0.35%	1.2%	0.34%
88.190.14.112	France		0.6%	0%				
95.130.11.214	France	196689	0.06%	0%	0.23%	1.26%	0.23%	1.3%
37.187.20.59	France	16276	0.12%	0%	8.12%	3.78%	1.4%	0.45%
198.27.97.223	Canada		0.09%	0%			0.098%	0%
89.46.100.162	Romania	58207	0%	0%	0.096%	0%	0.096%	0%
5.254.101.92	Romania	39743	0%	0%	1.25%	8.38%	0.046%	0%
46.23.70.195	United Kingdom	13213	0.21%	0%	1.03%	4.68%	0.21%	0%
37.247.52.27	Italy	34971	0.005%	0%	0.066%	0%	0.05%	0%
217.12.199.190	Ukraine	15626	0%	0%	0.093%	0.66%	0%	0%
212.186.51.184	Austria	6830	0.001%	0.009%	0.55%	0.16%	0.0013%	0.0097%
91.219.237.110	Hungary	56322	0%	0%	0.71%	1.04%	0.71%	1%
37.0.123.152	Russia	198310	0.12%	0%	0.12%	0%	0.12%	0%
46.28.110.129	Czech Republic	197019	0.19%	0%	1.36%	0.68%	0.26%	0.23%
218.251.112.170	Japan	17511	0.005%	0%	0.021%	0%	0.0054%	0%
Total			3.12%	0.01%	23.25%	25.56%	7.64%	3.66%

Table 6. Details of our participating Tor relays.